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Optimal selection of process parameters to reduce vibration during end milling of Al 356/SiC metal matrix composite

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Machining performances are strongly influenced by vibration which occurs due to the dynamic nature of machine tool structures. A self excited vibration commonly known as chatter is frequent debacle occurs during milling operations which cause worsening outcomes such as excessive tool wear, poor surface finish and reduced tool life. In this paper an effort has been tried to optimize the machining and geometrical parameters for reduced vibration using Taguchi method with grey relational analysis during end milling of Al356/SiC metal matrix composites. The twin channel piezoelectric accelerometer has been used to measure vibration. Acceleration amplitudes at two different positions, one in spindle and another in work piece holder have been recorded for each experiment. Analyses of variance (ANOVA) have been applied to find the prominent parameters and the optimal parameter combination for best average response and signal to noise (S/N) ratio. Grey relational analysis has been implemented to find the optimal permutation of machining and geometrical parameters by considering both responses (acceleration amplitude taken at two different positions) simultaneously. Confirmation tests established that the grey-based Taguchi method has been successful in optimizing the process parameter for reduced vibration.

Keywords: Taguchi method, Grey relational analysis, Vibration, Accelerometer, ANOVA, composites, HSS end mill

1 Introduction

A composite material replaces many conventional materials owing to its exceptional engineering properties. Metal matrix composites (MMC's) are extensively used composites and synthesized for diverse industrial purposes such as aerospace, automotive, defense, medical equipments and sport equipment industries. MMC's have outstanding mechanical properties such as lower density and light weight, lower coefficient of thermal expansion and high strength, stiffness, hardness, corrosion and wear resistance. Particle (SiC) reinforced aluminium (Al356) MMC are commercially available MMC received extensive awareness due to their inexpensive production. These composites are heterogeneous and their properties based on matrix properties, volume fraction of the reinforcement and the bonding strength between aluminium and SiC particles. Al/SiC particulate composites are commonly used for making piston, piston rings, connecting rod, cylinder liner, space structures, etc. The properties of Al/SiC have been explored by many researchers[1-4]. Even though MMC's are manufactured with near net-shaping methods, final finishing, machine operation is needed. The growing application of Al/SiC particulate composites demands a proficient and cost-effective machining of the materials for the required tolerance and surface finish. The machining of Al/SiC particulate composites are difficult in many aspects compared to common Al alloys. El-Galleb and Sklad[5, 6] studied the machinable properties of Al/SiC particulate composite based on tool performance and work piece surface integrity. Tool wear was found to be reduced using zero rake angle poly crystalline diamond tools with higher feed rate and cutting speed. Surface finish was found to be better at higher cutting speeds and lower feed rate and depth of cut. Jeyakumar *et al.*[7]investigated the influence of machining parameters on cutting force, surface roughness and tool wear while machining Al6061/SiC particulate composite using tungsten carbide end mill tools. Tamer *et al.*[8] presented the machinability study on aluminium alloy reinforce with the silicon carbide particles in varying proportions. Higher the addition of reinforcement particles shows improved mechanical properties but on machinability aspect, it resulted in excessive tool wear and increased surface roughness. Seeman *et al.*[9] investigated machinability characteristics such as tool wear and surface roughness of 20% SiCp LM25 Al

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meal matrix particulate composite. An empirical relationship has been established between the machinability characteristic and machining parameters which influence the machining conditions.

Due to the abrasive nature of SiC reinforcing particles, the machining of these composites is hard to cut which results increased vibrations. Vibrations cause destructive effects during machining to the cutting tool (excessive tool wear) and the work piece (poor surface finish). Different components of machine tool, different loading conditions, change in cutting tool geometry and wide range of process parameters results in a vibratory system with intricate dynamic performance. Hence a methodology to predict vibrations is very important to increase the performance of machining. Yasuhiro[10] developed a new system to detect chatter vibration without using accelerometer sensors. The proposed system uses servo driver information (angular velocity of the spindle using rotary encoder) to determine chatter vibration based disturbance torque. Lacerda and Lima[11] constructed a stability lobe diagram based on the milling test conducted for various combinations of depth of cut and spindle speed by positioning accelerometer at two different points. Zhang and Zhen[12] fabricated a cost effective microcontroller based data acquisition system to collect vibration signals for machine condition monitoring. Fan and Guangya[13] developed a magnetic actuator which does damping of vibration in machine tools and also evaluated online cutting forces during machining. Yuanming and Neil[14] demonstrated the possibility of reducing the work piece chatter during milling operation using piezoelectric active vibration control and further discussion on the realistic issues regards to the application of this technique was investigated. Arnaud and Daniel[15] employed eddy current sensors to evaluate the micro movement of a tool and the signals collected reveal that the vibration occurs during the machining process. Sadettin *et al.*[16] used accelerometer CSI 350 to collect the vibration signals in the feed direction and also established relation between vibration and tool wear.

End milling operation is a known metal cutting process which was engaged for machining flat, curved or irregular surfaces; profiles, contours and engraves on the surface; and slot and pockets in various components. This process engrosses discontinuous cutting due to non uniform chipped cross section. Thus, irregular cutting impact heavy loads and also fluctuating forces makes end milling operation subjected to chatter vibration. Chatter is disadvantageous due to its undesirable effects on the product quality, machining accuracy, tool life, machine tool bearings and machine tool life. These chatter vibrationstranspire due to lack of rigidity in the machine tool and cutting conditions. A tool monitoring system is needed to envisage the vibration based on the machining parameters to ensure better machining performance for good surface finish and minimized tool wear. Research analysis had been conceded out on the end milling operation using different work materials, tool materials and the various experimental designs. Thambu and Marimuthu[17] conducted machinability test of aluminium alloy (LM 24) combined with silicon carbide particles of varying percentage MMC's using end mill cutter. It was observed that the surface roughness and tool wear were higher with an increase in SiC percentage. Palanisamy *et al.*[18] employed artificial neural network technique to predict the chatter vibration while milling AISI 1020 steel. The occurrence of chatter vibration for a particular combination of machining parameter were predicted using a stability lobe diagram and dynamic stability were analyzed using Nyquist criterion. Klaus *et al.*[19] proposed a simulation concept to determine the effect of regenerative vibration that propelled in the workpiece and also presented a finite element model to analyze the dynamic behavior of work piece during milling operation. Subramanain *et al.*[20] developed a statistical empirical model for milling operation which relates the input machining parameter such as rake angle, nose radius, speed, feed and depth of cut to the output response vibration amplitude picked in the machine tool in two different positions. Prasad *et al.*[21] employed response surface methodology to optimize cutting parameters in milling operation to obtain lesser surface roughness and vibration amplitude. Panling *et al.*[22] illustrated the cutting force variation based on signal processing methods such as frequency domain, time domain and wavelet analysis to describe the influence of cutting speed on cutting stability during milling titanium alloy.

Obtaining the optimal combination of process parameters for better machining performance is of immense concern in manufacturing industries. Design of experimental technique can be employed to reduce the magnitude of experiments to correlate the input process parameters and output response. Taguchi method is a dominant statistical design of experimental tool for conducting experiments. It is used to analyze and optimize the levels of process parameters for the required performance characteristic.

For multiple performance characteristic, grey relational analysis yield a solution through combined grey relational grade. Rajmohan *et al.*[23] employed Taguchi method with grey relational analysis to determine the optimal combination of drilling parameter for better multiple performance characteristics. L_{18} orthogonal array was chosen for conducting the experiments. Siddhi *et al.*[24]optimized sintering process parameters for preparing aluminium, Silicon and fly ash combined composite using combined Taguchi method and grey relational analysis. Ahmet and Kenan[25] employed L27 orthogonal array for conducting experiments and grey relational analysis for multiple performance optimization while machining boron carbide particle reinforced MMC. Lin and Lin[26] optimized EDM machining parameters such as pulse on time, polarity, open discharge voltage discharge current, duty factor and dielectric field to obtain multiple better performances such as reduced metal removal rate, surface roughness and electrode wear rate using the Taguchi technique combined with grey relational analysis.

Earlier work pertains to the prediction of vibration amplitude employing response surface methodology[27] and optimized the machining parameters using grey-based Taguchi method [28] has been devised for aluminium alloy. From the above literature, it has found that most of the researchers did vibration analysis during machining of ferrous and non ferrous metals, not on the composites. Machinability studies conducted on composites were pertaining to reduce surface roughness and tool wear. The determination of vibration amplitude while machining composite materials has not been accounted so far. The geometry of end mill tool is very complex and research relevant to their influence on the stability of milling process has been limited and particularly for machining composite material yet to be explored. The composite materials Al356 reinforced with 5% SiC were considered in this paper. Currently this material is used in industries for making brake master cylinder, where end milling used for finishing operation. The main objective of this research is to determine the optimal level of machining and geometrical parameters such as cutting speed, feed rate, depth of cut, helix angle, nose radius and rake angle while machining Al356 with 5% SiC metal matrix composite. The Taguchi method was employed in conducting the experiments and grey relational analyses were employed for multiple response optimization.

2 Experimental Procedure

The experimental procedure is ordered in the following manner. The detail of preparation of composite work materials and vibration amplitude measurement was enumerated first. The selection of experimental design (Taguchi method) and selection of geometrical and machining parameters for conducting experiments was briefed next. Then, an outline of the optimization procedure for multiple responses using grey relational analysis was given.

2.1 Materials and Method of Preparation

Metal matrix composite was fabricated using the matrix material as aluminium alloy Al356 and reinforcing materials as silicon carbide particles of size approximately 40µm. The chemical composition of Al356 is presented in Table 1. The percentage of volume of silicon carbide particles used in the composites was fixed to be 5%.

Stir casting method was used for the fabrication of composite since it ensures the uniform distribution of the reinforcements. In the procedure of making the composites, the Al356 first melted at 700 ºC, after which the preheated silicon carbide was mixed with the molten aluminium alloy in atomic ratio using the stirring method. Sic is preheated to 800 ºC for 2 hours. After the SiC addition cryolite was added, which prevents agglomeration and helps in uniform deposition of the particulate within the matrix. The stirrer used to be a stainless steel stirrer which was coated with Zirconia. The coating was applied to avoid possible contamination of the molten metal. Since Aluminium produces a lot of dross and oxide during melting, degassing was involved through bubbling of argon through the melt to absorb hydrogen and other impurities. The period of chemical reaction was varied in steps up to 30 min. After the reaction, the composite was cast into a die which was preheated to 400 ºC. Hardness of prepared composite material is found to be 67.5 HB. The stir casting set up is shown in Fig. 1.

2.2 Vibration Measurement

Two main problems often meet with the end mill cutters which are related to rigidity are spring back and chatter. Spring back is effected by insufficient stiffness and the resulting deflection or deformation of

Table 1 — Chemical composition of LM25 aluminium alloy (mass fraction, %).

Si	Mg	Mn	Fe	Cu	Ni	Ti
7	0.33	0.3	0.5	0.1	0.1	0.2

Fig. 1 — Stir casting set up.

the cutter due to cutting forces. Excessive spring back (or elastic recovery) of the end mill cutter will end in a scratch marks during the tool forward and backward movement. Chatter is a resonant vibration that transpires due to vibrations of engagement of the tool and work piece during machining happens to be natural frequency of the machine tool in which a small excitation generates large amplitudes. Under this condition excited pounding between the tool and workpiece greatly increases tool wear, surface roughness and damage the machine tool. Chatter can occur either during the feeding or retracting motions. Many parameters can be identified for the generation of the chatter vibration, in this study the geometrical parameters and machining conditions have been taken into consideration.

The vibrations were picked at two different positions using piezoelectric accelerometer. The accelerometer dynamically collects the raw vibration signal data obtained during interaction of tool and workpiece. The output raw signals of accelerometer senses the acceleration in terms of MV (10 MV = 1m/s^2) need to be amplified. An integrated circuit (IC) interface is used to amplify the voltage signal recorded trough accelerometer. The signals were recorded in data acquisition system which can be analyzed further. Lab view evaluation software was employed using fast fourier transfer function digitizes the input signals at various discrete points and convert into a waveform and frequency spectrum. It uses NI9234, analog to digital (A/D) and digital to analog (D/A) converters of 24 bits, dynamic range of 130 dB and the sampling rate / channel is up to 102 kHz. The waveform concise for 2 seconds the occurrence of pulse periodically in terms of displacement or velocity or acceleration. The spectrum displays the amplitude of vibration with respect to frequency and was obtained using FFT

Fig. 2 — Data acquisition system to acquire vibration signals.

analysis of waveform. The peak value of the spectrum denotes the maximum vibration induced and this value during the milling operation was noted. The data acquisition arrangement to acquire is shown in the Fig. 2.

2.3 Experimental Design

The classical experimental design is too complex and large number of experiments needed to be conducted with increase in process parameter. The Taguchi method is an organized application of design of experiment technique for the purpose of achieving high quality with low cost. This method yields a solution through specially designed orthogonal arrays to cram the complete process parameter space with a limited number of experiments. Thus, it has been a significant tool for increasing productivity during research and development. Taguchi suggests the application of loss function to manipulate the performance characteristics of the process. The loss function indicates the variation between the experimental and desired value. The quantified loss function value is then altered into a signal-to-noise ratio (S/N), where the term signal represents the desirable mean value and the term noise represent undesirable standard deviation value. Depending on the requirement of output performance characteristics in the analysis of S/N ratio, three categories identified are lower is better, nominal is better and higher is better. The objective concerned with this paper is to minimize vibration, hence lower is better is implemented. Lower the better S/N ratio for output performance characteristics can be calculated using the equation 1.

S/N ratio $\eta = -10\log\frac{1}{n}\left(\sum_{i=0}^{n} y_i^2\right)$ …(1)

where, n is the number of trials of experiments and y_i is i^{th} measured value.

The values for the S/N ratio for each level of the input parameters were evaluated based on the S/N ratio analysis. The larger S/N ratio computed for the particular level indicates better performance characteristics. Additionally, analysis of variance (ANOVA) was employed to determine the significant process parameters that enhance the better performance characteristics. Thus the optimum levels of geometrical and machining parameters can be obtained. The process parameters in the milling process are geometrical taxonomy and machining conditions that influence the dynamic stability during machining operation. In the current study, the process parameter (three levels for each parameter) considered were geometrical parameters such as helix angle, nose radius and radial rake of cutting tool and machining parameters such as cutting speed, feed rate and depth of cut. L27 orthogonal design array was deployed to conduct experiments. The process parameter range was constrained within the limits of machine tool through trail runs. The process parameter and its level are shown in the Table 2.

2.4 Grey Relational Analysis

Taguchi method is used to find the optimum level of process parameters for single output performance characteristics. Nevertheless, multi performance characteristic response optimization was not simple as a single response characteristic optimization. The upper S/N ratio for one output response may have a lesser S/N ratio for another output response. Hence, the cumulative estimation of the S/N ration is needed for the multi performance characteristic response optimization. Grey relational analyses yield a solution that has been adapted in this study.

In this analysis, the following steps were followed:

Table 2 — Parameters and its levels.

Parameter	Units	levels 1	2	3
Helix angle (α)	0	40	45	50
Nose radius (R)	mm	0.4	0.8	1.2
Rake angle (γ)	0	8	12	16
Cutting speed (N)	m/min	30	60	90
Feed rate (F)	mm/rev	0.03	0.04	0.05
Depth of cut (Y)	mm	0.5	1	1.5

a. Normalize the signal to noise ratio of the experimental value obtained by picking acceleration amplitude at two different positions, one in the spindle (channel I) and another in work piece holder (channel II) and the resulting normalized value which varies between 0 and 1. If x_{ij} is the normalized S/N ratio for the i^{th} performance characteristic in the j^{th} experiment then x_{ij} can be expressed as

$$x_{ij} = \frac{\max_j \eta_{ij} - \eta_{ij}}{\max_j \eta_{ij} - \min_j \eta_{ij}} \quad …(2)$$

where; η_{ij} is the i^{th} experimental result in the jth trial, $\max_j \eta_{ij}$ and $\min_j \eta_{ij}$ are maximum and minimum values of signal to noise ratio.

b. From the normalized value obtained using equation 2, the grey relational coefficient is calculated to state the connections between the desired and actual experimental values. The grey relational coefficient is obtained using the following equation

$$\gamma_{ij} = \frac{\Delta\min + \zeta\Delta\max}{\Delta\eta ij + \zeta\Delta\max} \quad …(3)$$

where γ_{ij} is the i^{th} measured value in the j^{th} experiment, 'Δ min' and 'Δmax' is the minimum and maximum value of the normalized signal to noise ratio of i^{th} measured value, ζ is the distinguishing coefficient. The value of ζ can be adjusted with systematic actual need and defined in the range of 0 and 1. $\zeta \in (0, 1)$. Normally the value is assumed as 0.5.

c. Grey relational grade is obtained by averaging grey relational coefficient. Thus, throughhgray relational grade multiple performance output characteristics are converted into single performance output. The grey relational grade (δ_j) was calculated using the following equation.

$$\delta_j = \frac{1}{m}\sum_{i=1}^{m} w_i \gamma_{ij} \quad …(4)$$

where, m is the number of output performance characteristics.

d. Ranking is given based on the value of the grade. Optimal level of process parameters is identified for which the value of the gray relational grade is maximized.

e. Confirmation experiment is conducted corresponding to optimal level in order to validate the result.

3 Experimental Set- up

The experiments were conducted on DMC 835V CNC milling machine with high-speed steel end mill cutter with four flutes under dry condition. The work piece material was aluminium metal matrix composite (Al356+5% sic). The dimensions of the work piece specimen were taken as 50mm × 50mm × 50mm.For conducting the experiments L27 orthogonal array was used. The orthogonal array contains 27 rows and 6 columns. In order to reduce experimental error the experiments are conducted in a completely random manner. Two piezoelectric accelerometer sensors were used, one is fixed in the spindle (channel I) and another one is fixed in the work piece holder (channel II) to pick the vibration amplitude in terms of acceleration during milling. The analog vibration signals picked up by these sensors is then digitized and then analyzed using lab view evaluation software. The acceleration amplitude of vibration picked up during milling was recorded in the form of a waveform and frequency spectrum. The signals are captured continuously, but three peak values of amplitudes recorded by a sensor in the spindle and workpiece terminal are noted and tabulated in Table 3 and Table 4 as channel I and channel II, respectively. The experimental setup and location of accelerometer is shown in the Fig. 3.

4 Results and Discussion

4.1 Analysis of S/N Ratio

Table 3 and 4 shows the data observed for three repetitions during measurement of acceleration amplitude in two different positions (channel I and II). The average value of the amplitudes is evaluated and noted down. The signal to noise ratios are calculated using the Eq. (1) by taking into consideration the lower is better characteristic and are noted in Tables 3 and 4. At a particular parameter level the average

Table 3 — Experimental result for acceleration amplitude for channel I.

S.No	Control parameters						Acceleration amplitude m/sec^2 Channel-I (Spindle)				S/N ratio (η)(dB)
	α	r	γ	N	F	Y	Trial1	Trial2	Trial3	Average	
1	1	1	1	1	1	1	3.8	3.6	4.8	4.0666	-12.256538
2	1	1	1	1	2	2	3.8	3.5	3.82	3.7066	-11.386437
3	1	1	1	1	3	3	4.1	3.9	3.97	3.9900	-12.021331
4	1	2	2	2	1	1	9	9.5	8.9	9.1333	-19.216171
5	1	2	2	2	2	2	9.4	9.4	9.4	9.4000	-19.462557
6	1	2	2	2	3	3	10.75	9.75	9.5	10.0000	-20.012648
7	1	3	3	3	1	1	11.56	11	11.5	11.3533	-21.104591
8	1	3	3	3	2	2	13.8	13	13.25	13.3500	-22.512346
9	1	3	3	3	3	3	15.5	17.5	16.5	16.5000	-24.360301
10	2	1	2	3	1	2	11.25	11.75	11	11.3330	-21.090439
11	2	1	2	3	2	3	11.75	11.25	12.25	11.7500	-21.405997
12	2	1	2	3	3	1	10.1	10.3	11	10.4666	-20.402066
13	2	2	3	1	1	2	5.35	5.45	5.35	5.3833	-14.621358
14	2	2	3	1	2	3	4.8	5.15	5.25	5.0666	-14.100739
15	2	2	3	1	3	1	8.9	10.5	8.95	9.4500	-19.535382
16	2	3	1	2	1	2	9.8	10.25	10.4	10.1500	-20.13206
17	2	3	1	2	2	3	11.2	10.9	10.5	10.8666	-20.72495
18	2	3	1	2	3	1	9.75	10.8	10.5	10.3500	-20.306705
19	3	1	3	2	1	3	12.3	11.4	12.4	12.0330	-21.61378
20	3	1	3	2	2	1	10.5	10.9	10.25	10.5500	-20.467845
21	3	1	3	2	3	2	11.3	12	11.7	11.6660	-21.341558
22	3	2	1	3	1	3	23.4	21	22.5	22.3000	-26.974647
23	3	2	1	3	2	1	12	11	10.9	11.3000	-21.06995
24	3	2	1	3	3	2	22	21	21.5	21.5000	-26.650335
25	3	3	2	1	1	3	6.85	5.2	5.45	5.8333	-15.385109
26	3	3	2	1	2	1	3.52	5.5	3.6	4.2066	-12.679567
27	3	3	2	1	3	2	6.1	6.75	5.6	6.1500	-15.802881

Table 4 — Experimental result for acceleration amplitude for channel II.

S.No	Control parameters α	r	γ	N	F	Y	Acceleration amplitude m/sec^2 Channel-II (Work piece) Trial1	Trial2	Trial3	Average	S/N ratio (η)(dB)
1	1	1	1	1	1	1	0.37	0.33	0.175	0.29166	10.355439
2	1	1	1	1	2	2	0.42	0.41	0.405	0.41166	7.7080895
3	1	1	1	1	3	3	4.3	4.65	5.5	4.8166	-13.7022
4	1	2	2	2	1	1	4.6	5.4	5.1	5.0333	-14.05574
5	1	2	2	2	2	2	0.625	0.625	0.9	0.71666	2.7538284
6	1	2	2	2	3	3	2.25	1.9	1.75	1.9666	-5.9236184
7	1	3	3	3	1	1	0.455	0.465	0.45	0.4566	6.807204
8	1	3	3	3	2	2	0.7	0.7	0.74	0.71333	2.9311161
9	1	3	3	3	3	3	2.1	1.8	2.2	2.0333	-6.1944118
10	2	1	2	3	1	2	0.545	0.55	0.525	0.54	5.3503876
11	2	1	2	3	2	3	0.45	0.485	0.44	0.45833	6.7686827
12	2	1	2	3	3	1	0.58	0.475	0.44	0.49833	5.9881494
13	2	2	3	1	1	2	0.32	0.33	0.3	0.31666	9.9812212
14	2	2	3	1	2	3	0.33	0.33	0.32	0.3266	9.7169993
15	2	2	3	1	3	1	0.28	0.245	0.23	0.25166	11.953495
16	2	3	1	2	1	2	0.418	0.41	0.35	0.39266	8.093658
17	2	3	1	2	2	3	0.64	0.546	0.55	0.5786	4.7270701
18	2	3	1	2	3	1	0.46	0.44	0.475	0.45833	6.7721236
19	3	1	3	2	1	3	0.546	0.575	0.51	0.54366	5.2829718
20	3	1	3	2	2	1	0.36	0.36	0.35	0.3566	8.9539909
21	3	1	3	2	3	2	0.485	0.49	0.48	0.485	6.2848575
22	3	2	1	3	1	3	14	13.6	14.5	14.033	-22.946205
23	3	2	1	3	2	1	0.55	0.53	0.55	0.5433	5.2973655
24	3	2	1	3	3	2	4	4	5.45	4.4833	-13.131815
25	3	3	2	1	1	3	0.38	0.39	0.36	0.3766	8.4760972
26	3	3	2	1	2	1	0.24	0.175	0.185	0.2	13.891625
27	3	3	2	1	3	2	0.43	0.35	0.33	0.37	8.5771484

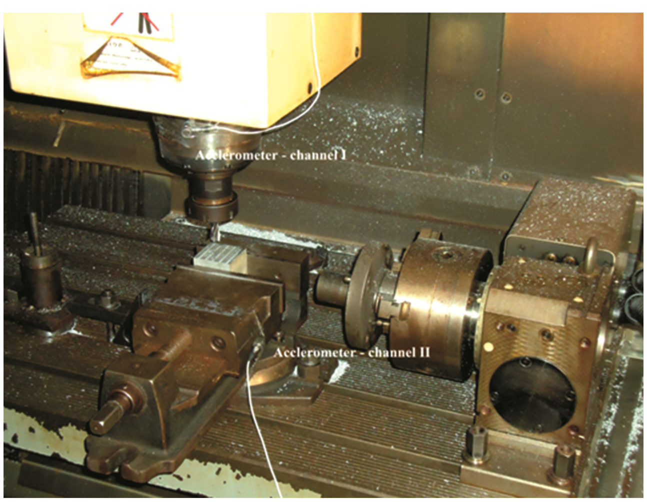

Fig. 3 — Experimental set up – accelerometer.

value of acceleration amplitude was calculated in order to find out the above measured values at each parameter level. In the integrated manner the response table for mean acceleration amplitudes for each level of process parameters was created. Table 5 and 6 gives the calculated average value of acceleration amplitudes (channel I and II) for each control parameter at each level. By following the same procedure the S/N ratio response for acceleration amplitudes (channel I and II) for each level of process parameter was calculated. The mean value of the S/N ratio for each level of geometrical and machining parameters was calculated and is tabulated in Tables 7 and 8.

From Table 5, based on the mean value of acceleration amplitude (channel I) for each level, the difference between the maximum and minimum value was calculated. The parameters with the highest difference were found to be most significant and are ranked progressively. The level with least value for each parameter was found to be optimum. From Table 5, the optimal combination that will give minimum acceleration amplitude (channel I) is noted as α1 r1 γ2 N1 F2 Y1. The most significant parameters are rated as cutting speed – rank 1, helix angle – rank 2, nose radius – rank 3, rake angle - rank4, feed rate - rank5

Table 5 — Mean response for acceleration amplitude for channel- I.

Levels	α	r	γ	N	F	Y
1	9.0555*	8.8402*	10.9144	5.317*	10.1762	8.9863*
2	9.424	11.5037	8.697*	10.461	8.9107*	10.2932
3	11.7265	9.8622	10.5947	14.4281	11.1192	10.9266
Δ	2.671	2.6635	2.2174	9.1111	2.1785	1.9403
Rank	2	3	4	1	5	6

*Optimum levels

Table 6 — Mean response for acceleration amplitude for Channel II.

Levels	α	r	γ	N	F	Y
1	1.81775	0.93239	2.9855	0.80854*	2.4426	0.8762*
2	0.42255*	3.1809	1.1315	1.17568	0.4783*	0.9278
3	2.4933	0.62036*	0.6167*	2.7494	1.707	3.1131
Δ	2.07075	2.56054	2.3689	1.94086	1.9643	2.2369
Rank	4	1	2	6	5	3

Table 7 — S/N ratio response table for acceleration amplitude for Channel- I.

Levels	α	r	γ	N	F	Y
1	-18.038*	-18.00*	-19.06	-14.20*	-19.15	-18.56*
2	-19.15	-20.18	-18.30*	-20.36	-18.34*	-19.22
3	-20.22	-19.22	-20.00	-22.84	-20.00	-19.62
Δ	2.19	2.18	1.70	8.64	1.66	1.06
Rank	2	3	4	1	5	6

*Optimum levels

and depth of cut – rank 6. From Table 7, the significant parameters and the optimum levels for minimum acceleration amplitude (channel I) were evaluated using average values of S/N ratio. Similar results were obtained.

From Table 6, based on the mean value of the acceleration amplitude (channel II) at each level, the difference between the maximum and minimum value was calculated. The maximum difference will give the most significant parameters, and rank for the significant parameters are allotted. From Table 6, optimum parameter level combination that will give minimum acceleration amplitude (channel II) is observed as α 2 r3 γ3 N1 F2 Y1. The most significant parameters are rated as nose radius – rank 1, rake angle – rank 2, depth of cut – rank 3, helix angle – rank 4, feed rate – rank 5 and cutting speed – rank 6. From Table 8, the significant parameters and the optimum levels for minimum acceleration amplitude (channel II) were evaluated using average values of S/N ratio. Similar results was obtained. The effect of process parameters resulting from the optimization process is plotted in Figs 4, 5, 6 and 7.

Table 8—S/N ratio response for acceleration amplitude for channel- II.

Levels	A	B	C	D	E	F
1	0.78	4.78	-0.80	7.44*	1.93	6.01*
2	7.71*	-1.82	3.54	2.54	6.97*	4.28
3	2.30	6.01*	6.20*	1.01	0.07	-0.95
Δ	6.93	7.83	7.00	6.43	6.90	6.96
Rank	4	1	2	6	5	3

*Optimum levels

4.2 Analysis of Variance (ANOVA)

A statistical analysis of variance (ANOVA) was performed to determine the significance and influence of process parameters on quality characteristics. Equations (5) and (6) were used to find out the total sum of the squared deviations (SS_T) from the total mean S/N ratio and also the percentage contribution of variance (ρ), respectively.

$$ss_T = \sum_{i=t}^{n} (\eta_i - \eta_n)^2 \quad \ldots(5)$$

$$\rho = \frac{ss_D}{SS_T} \quad \ldots(6)$$

where, n represents the number of experiments in the orthogonal array, η_i represents the S/N ratio of the ith experiment, η_n represents the total mean S/N ratio and SS_D represents the sum of the squares of deviation. F-ratio (the ratio between the mean square error to the residual) in ANOVA used to determine the most significant process parameter that influences the output performance characteristic. Higher the F-ratio value will indicate that the parameter will influence more on the output performance characteristic. The significance level (significant or non significant) of the process parameter will be indicated by ρ – value. Lower the ρ – value will indicate that the parameters were more significant.

The results of ANOVA for acceleration amplitude (channel I & II) are given in Table 9 and 10, respectively.

From Table 9, the most significant parameters that influence acceleration amplitude (channel I) were given as helix angle, α = 6.5328%, nose radius, r= 5.6293%, rake angle, γ = 4.4797%, cutting speed, N = 65.065%, feed rate, F = 3.8287% and depth of cut, Y = 3.0526%. From the Table 10, the most significant parameters that influence acceleration amplitude

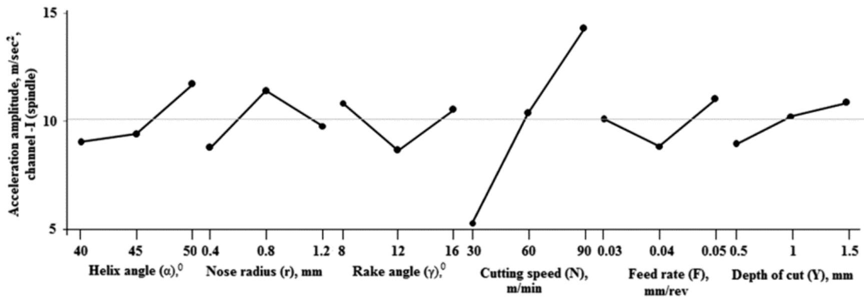

Fig. 4 — Effect of process parameters on acceleration amplitude – channel I.

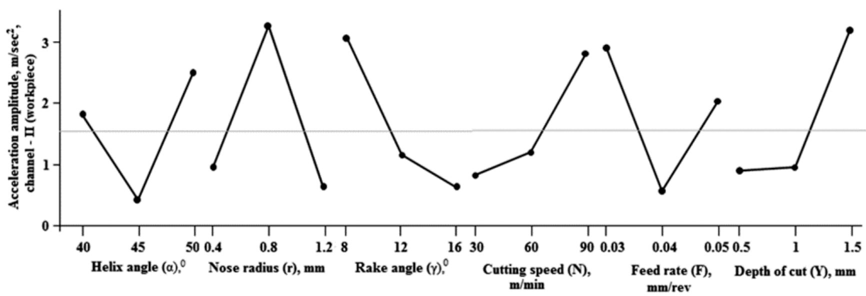

Fig. 5 — Effect of process parameters on acceleration amplitude – channel II.

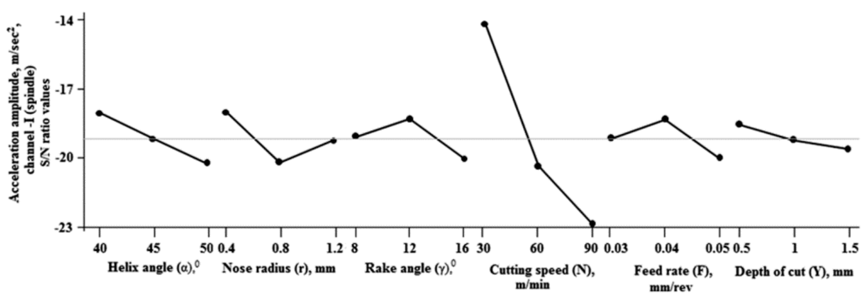

Fig. 6 — Effect of process parameters on S/N ratio of acceleration amplitude – channel I.

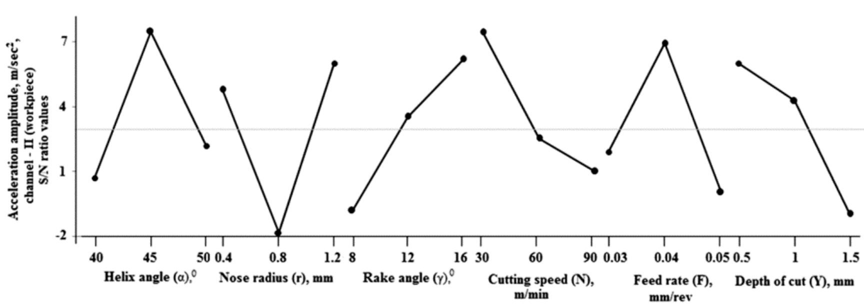

Fig. 7 — Effect of process parameters on S/N ratio of acceleration amplitude – channel II.

(channel II) were given as helix angle, α = 8.53%, nose radius, r = 15.02%, rake angle, γ = 12.03%, cutting speed, N = 7.86%, feed rate, F = 8.29%, depth of cut, Y = 9.86%.

4.3 Grey Relational Analysis

The optimal combination of process parameters for reduced acceleration amplitude (channel I & II) were determined using Taughi method. The optimization of process parameters considering multiple performance characteristic was required. Grey relational analysis was used to determine the optimal combination of machining and geometrical parameters by considering both responses i.e. acceleration amplitude (channel I & II) simultaneously.

Table 9 — ANOVA results for acceleration amplitude for channel- I.

Parameters	DF	SS	F	p	p(%)	Sig
α	2	37.715	4.01	0.042	6.5328	2
r	2	32.499	3.45	0.06	5.6293	3
γ	2	25.862	2.75	0.098	4.4797	4
N	2	375.632	39.91	0	65.065	1
F	2	22.104	2.35	0.132	3.8287	5
Y	2	17.623	1.87	0.19	3.0526	6
Error	14	65.881				
Total	26	577.316				

S = 2.16928 R-Sq = 88.59% R-Sq (adj) = 78.81%

Table 10 — ANOVA results for acceleration amplitude for channel-II.

Parameters	DF	SS	F	p	p(%)	Sig
α	2	18.239	1.56	0.245	8.53	4
r	2	32.123	2.74	0.099	15.02	1
γ	2	25.718	2.19	0.148	12.03	2
N	2	16.812	1.43	0.271	7.86	6
F	2	17.728	1.51	0.254	8.29	5
Y	2	21.097	1.8	0.202	9.86	3
Error	14	82.064				
Total	26	213.781				

S =2.42110 R-Sq =61.61% R-Sq (adj) = 28.71%

The S/N ratio calculated for acceleration amplitude (channel I & II) was normalized using Eq. 2. This data pre-processing was required, since the range and unit in one data sequence may differ from others. The normalized value converts the original sequence into to a set of comparable sequence. Using Eq. (3) the grey relational coefficient was calculated and the corresponding grade and rank were evaluated. As a result, optimization of the complicated multiple performance characteristic can be transformed into an optimization of single gray relational grade. Thus the Gray relational grade can be used as the overall evaluation of experimental data for the multiple performance characteristic. The highest grey relational grade evaluated was close to the optimal condition. The normalized value, grey relational coefficient and its grade and rank were tabulated in the Table 11. From the Table 11, it is observed that the experiment 26 gives the optimal combination of machining and geometrical parameters for minimum acceleration amplitude (channel I & II). Their combination is α3 r3 γ2 N1 F2 Y1.

Since the experimental design is orthogonal, the effect of each machining and geometrical parameters on the grey relational grade at different levels are independent. The difference between the maximum and minimum values of mean value of the grey relational grade at each level was calculated and is shown in the Table 12. The maximum difference will give the most significant parameters, and rank for the significant parameters are allotted. From Table 12, optimum parameter level combination that gives minimum acceleration amplitude (channel I & II) was observed as α2 r1 γ2 N1 F2 Y1. The most significant parameters are rated as cutting speed - rank 1, rake angle - rank 2, helix angle – rank 3, nose radius – rank 4, depth of cut - rank 5 and feed rate – rank 6. The effect of process parameters on grey relational grade is depicted in the Fig. 8.

An ANOVA result for grey relational grade was shown in Table 13. From Table 13 it was observed that the order of significant parameters that influence acceleration amplitude (channel I & II) are cutting speed, N (42.844%) ; rake angle, γ (17.48%); helix angle, α (14.17%); nose radius, r (11.03%); depth of cut, Y (1.54%); and feed rate, F (1.42%).

4.4 Confirmation Test

The optimal combination of process parameters was evaluated, the final step is to predict and verify the improvement of the performance of multiple characteristic using these optimal levels. From grey based Taguchi method the optimal combination evaluated was α1 r2 γ2 N1 F2 Y1. The result of ANOVA indicates that all the process parameters were significant in influencing the response. Thus all parameters were included in predicting estimated grey relational grade. Using the optimal level of the design parameters, the estimated grey relational grade was calculated as:

$$\delta' = \delta_m + \sum_{i=1}^{q} (\delta_i - \delta_m) \quad \ldots(7)$$

q

where, δ' is grey relational grade for predicting the optimal parameters, δ_i is the average grey relational grade of the optimal level of parameters, δ_m is the mean value of grey relational grade and q is the number of machining and geometrical parameters. Grey relational grade for predicting optimal machining and geometrical parameters can be calculated as follows:

$$\delta' = \delta_m + \sum_{i=1}^{6} (\delta_i - \delta_m) = 0.82134 \quad \ldots(8)$$

Table 11 — Normalized, grey relational coefficient, grade and rank value.

S.No	Normalized Channel-I	Normalized Channel-II	Grey coefficient Channel-I	Grey coefficient Channel-II	Grade	Rank
1	0.944157	0.923046	0.899534	0.86662	0.883077	3
2	1	0.849667	1	0.768837	0.884419	2
3	0.959245	0.256223	0.924633	0.402001	0.663317	9
4	0.497712	0.246423	0.498859	0.398859	0.448859	24
5	0.481907	0.712346	0.491114	0.634797	0.562955	21
6	0.44662	0.471827	0.474662	0.4863	0.480481	23
7	0.376574	0.824697	0.445067	0.740408	0.592738	13
8	0.286269	0.71726	0.411953	0.638782	0.525367	22
9	0.167727	0.464321	0.375299	0.482775	0.429037	25
10	0.377482	0.784317	0.445427	0.698633	0.57203	17
11	0.357239	0.823629	0.437537	0.739239	0.588388	15
12	0.421639	0.801994	0.463667	0.716327	0.589997	14
13	0.792459	0.912673	0.706673	0.851315	0.778994	5
14	0.825855	0.90535	0.741681	0.84083	0.791255	4
15	0.477235	0.96734	0.488871	0.938685	0.713778	8
16	0.43896	0.860354	0.471236	0.781683	0.626459	11
17	0.400927	0.76704	0.454929	0.682165	0.568547	19
18	0.427756	0.823724	0.466312	0.739343	0.602828	12
19	0.34391	0.782448	0.432492	0.696814	0.564653	20
20	0.41742	0.884201	0.461859	0.811953	0.636906	10
21	0.361373	0.810218	0.439125	0.724867	0.581996	16
22	0	0	0.333333	0.333333	0.333333	27
23	0.378796	0.782847	0.445949	0.697202	0.571575	18
24	0.020827	0.272032	0.338027	0.407177	0.372602	26
25	0.743466	0.870955	0.660909	0.794855	0.727882	6
26	0.917021	1	0.857663	1	0.928832	1
27	0.716667	0.873755	0.638298	0.79841	0.718354	7

Table 12 — Grey relational grade response.

LEVEL	α	r	γ	N	F	Y
1	0.6078	0.6627*	0.51179	0.7677*	0.6142	0.66*
2	0.672*	0.5615	0.62419*	0.5637	0.6731*	0.6248
3	0.566	0.6355	0.62385	0.5083	0.57724	0.5618
Δ	0.106	0.1012	0.1124	0.2594	0.0958	0.0982
Rank	3	4	2	1	6	5

*Optimum levels

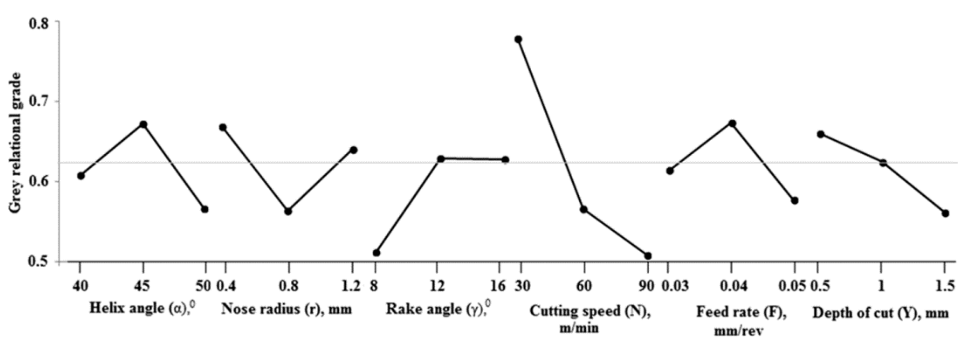

Fig. 8 — Effect of process parameters on grey relational grade.

Table 13 — ANOVA for grey relational grade.

Parameters	DF	SS	F	p	p(%)	Sig
α	2	0.058	8.61	0.004	14.169	3
r	2	0.04515	6.7	0.009	11.03	4
γ	2	0.07156	10.62	0.002	17.48	2
N	2	0.17538	26.04	0	42.844	1
F	2	0.00582	0.86	0.443	1.422	6
Y	2	0.00629	0.93	0.416	1.537	5
Error	14	0.04715				
Total	26	0.40935				

S = 0.0217345 R-Sq = 89.12% R-Sq(adj) = 79.80%

Table 14 — Confirmation experiment.

	Initial parameter taken	Optimal parameter from orthogonal array	Optimal machining parameters	
			Predicted	Experiment
Level	α1 r2 γ2 N2 F3 Y3	α2 r1 γ2 N1 F2 Y1	α2 r1 γ2 N1 F2 Y1	α2 r1 γ2 N1 F2 Y1
Acceleration amplitude (channel I)	10.00 m/sec ^{2}	4.2066 m/sec ^{2}		4.015 m/sec ^{2}
Acceleration amplitude (channel II)	1.966 m/sec ^{2}	0.2 m/sec ^{2}		0.183 m/sec ^{2}
Gray relational grade	0.48048	0.9288	0.9596	0.961

*Grey relational grade improved by 48.05%

The confirmation experiment was conducted by setting an optimal combination of machining and geometrical parameters as α1 r2 γ2 N1 F2 Y1.

Table 14 shows the comparison of the acceleration amplitude between the initial parameter levels and optimal parameter levels. It was found the optimal parameter level combination reduces the acceleration amplitudes (channel I and II) in the grey relational grade reduced for about 48%.

5 Conclusions

Acceleration amplitude was measured as a performance measure to access the, quality of machining of composite material. In this paper, the grey-Taguchi method was employed to determine the optimum values of machining and geometrical parameters for minimum acceleration amplitude. Conclusions derived, obtained from the experimental and analytical results were summarized below as:

(i) By using Taguchi method, the effect of machining and geometrical parameters on acceleration amplitude was calculated. The cutting speed and the rake angle were found to be the most significant parameter that influences acceleration amplitude picked at the spindle and workpiece locations respectively. The optimal values of machining and geometrical parameters for minimum acceleration amplitude were determined

(ii) To determine the optimum values of machining and geometrical parameters for two different performance characteristics (i.e. Acceleration amplitude acquired through channel I &II) the grey relational analysis was conducted. Cutting speed was found to be the most significant parameter. The optimum combinations of machining and geometrical parameter that gives minimum acceleration amplitude were determined, and it was found to be α2 r1 γ2 N1 F2 Y1

(iii) Confirmation experiments were conducted to calculate the improvement in the output performance characteristics by using grey-Taguchi method. The optimal combination parameter was compared with the initial parameter and it was found that there was significant improvement of grey relation grade

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